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THESIS

USING EXPERIMENTAL DESIGN AND DATA ANALYSIS TO STUDY THE ENLISTED SPECIALTY MODEL FOR THE U.S. ARMY G1

by

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June 2010

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Every month the U.S. Army G1 uses an Enlisted Specialty (ES) model consisting of a simulation and an optimization to forecast the Army's enlisted manpower program by Military Occupational Specialty and grade. The model is responsible for operating a 30.64 billion dollar manpower program that currently manages 460,000 enlisted Soldiers. The research in this thesis studies the objective function coefficients associated with decision variables in the ES optimization model. Experimental design and analysis techniques were used to study how changes in the coefficients affect the assignment of current enlisted soldiers to vacant positions in the U.S. Army. Results of the thesis show that by adjusting eight of the coefficients in the optimization model, the deviation between authorizations and inventory can be reduced by 14%. This improves the Army's force structure alignment and ensures the Army is ready to fight the nation's wars.

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USING EXPERIMENTAL DESIGN AND DATA ANALYSIS TO STUDY THE ENLISTED SPECIALTY MODEL FOR THE U.S. ARMY G1

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ABSTRACT

Every month the U.S. Army G1 uses an Enlisted Specialty (ES) model consisting of a simulation and an optimization to forecast the Army’s enlisted manpower program by Military Occupational Specialty and grade. The model is responsible for operating a 30.64 billion dollar manpower program that currently manages 460,000 enlisted Soldiers. The research in this thesis studies the objective function coefficients associated with decision variables in the ES optimization model. Experimental design and analysis techniques were used to study how changes in the coefficients affect the assignment of current enlisted soldiers to vacant positions in the Army. Results of the thesis show that by adjusting eight of the coefficients in the optimization model, the deviation between authorizations and inventory can be reduced by 14%. This improves the U.S. Army’s force structure alignment and ensures the Army is ready to fight the nation’s wars.

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LIST OF ACRONYMS AND ABBREVIATIONS

2FI	Two Factor Interactions
A2SF	Active Army Strength Forecaster
AAMMP	Active Army Military Manpower Program
APAS	Analyst Projection Assistance System
BCT	Basic Combat Training
CSV	Comma Separated Values
D-Opt LHD	D-Optimal Latin Hypercube design
DAPE-PRS	Department of the Army Personnel Plans, Resources and Strength
DMPP	Directorate of Military Personnel Policy
DOX	Design of Experiments
E3-E9	Enlisted pay grade
EG	Enlisted Grade
ES	Enlisted Specialty
ETS	Estimated Time of Separation
GUI	Graphical User Interface
HRC	Human Resources Command
IA	Individuals Account
LHD	Latin Hypercube Design
MIP	Mixed Integer Program
MOS	Military Occupational Specialty
MOSLS	Military Occupational Specialty Level System
MOSS	Military Occupational Specialty Shred
NPS	Non Prior Service
OFM	Officer Forecast Model
OSD	Operating Strength Deviation
OSUT	One Station Unit Training
PMAD	Personnel Management Authorization Document
PML	Programmed Managed Loss

POF	Program Objective Forces
PS	Prior Service
Reclass	Changing from one MOS to another
SAS	Statistical Analysis Software
SEED	Simulation Experiments & Efficient Design
SL1	Skill Level One Soldier
THS	Transients, Holdees, and Students
TRADOC	Training and Doctrine Command
TTHS	Trainees, Transients, Holdees, and Students
USC	United States Code
VBU	Valid but Unauthorized

EXECUTIVE SUMMARY

The U.S. Army G1 is responsible for developing, managing, and executing all manpower and personnel plans, programs, and policies for the Army. In order to accomplish a portion of this task, the G1 uses a very large, complex mathematical model known as the Enlisted Specialty (ES) model. The total annual Army manpower budget is 46 billion dollars and the enlisted Soldier annual budget is 30.64 billion dollars. The ES model is a vital piece in managing the enlisted Soldiers.

The ES model forecasts the future enlisted force for a seven year projection using historical data to determine rates and factors for changes. This projection is responsible for 460,000 enlisted Soldiers that are segregated into approximately 190 occupational specialties and numerous subspecialties, their different ranks, and years of service. The model, consisting of a simulation component and an optimization component, calculates the future force and minimizes the deviation between the Soldiers on hand and the authorized positions. The model itself takes into account 859,633 variables and calculates projections against 224,473 constraints.

The thesis work presented here uses design of experiments and data analysis to study the optimization component of the ES model. Specifically, the purpose of this thesis is to evaluate objective function coefficients that place weights on decision variables. The research contained in this thesis uses statistical techniques to

manipulate thesis weights in an attempt to reduce the deviation between the on hand quantity of Soldiers and the authorized positions.

The Enlisted Specialty model was deployed on Naval Postgraduate School computers in order to exploit multiple processers and advanced statistical methods of analysis. Several different types of analytical tools were used to provide valuable insight into the ES model. The analysis resulted in recommended changes to current practices of using the ES model. The suggested changes demonstrated that a 14.6% decrease in the deviation could be achieved.

The research and methodology developed in this thesis used September 2009 data to illustrate that lower deviation could be achieved through manipulation of the weighting coefficients for the decision variables in the optimization portion of the ES model. The proposed changes to the coefficient values were sent to the Army G1 to be implemented on the March 2010 data set. The suggested changes to the coefficients resulted in a reduction of the deviation of 18.7%. This is equivalent to an average drop of 8,355 miss aligned Soldiers (equivalent to two combat brigades) a month for the seven-year planning horizon. The suggested changes resulting from this thesis illustrated that a substantial drop in the deviation between authorizations and on hand strength can be achieved. Further testing continues and the proposed changes to the model are still under review at the Army G1 to examine the overall feasibility in making the changes set forth.

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I. INTRODUCTION

A. OVERVIEW

Title 10, United States Code (USC), provides the authority for personnel strengths for each of the armed services (2010). The Army G1 is responsible for developing, managing and executing all manpower and personnel plans, programs and policies—all Army Components—for the entire Army team (G1 Mission Statement, 2010). As of March 2010, there were approximately 559,783 Army Soldiers on active duty, of which, roughly 460,000 were enlisted (Defense Manpower Data Center, 2010). The enlisted population is extremely diverse in terms of their Military Occupational Specialty (MOS) and the amount of training each of those jobs require. Of the approximate 190 MOSs available for enlisted Soldiers the training for these occupations ranges anywhere from 13 weeks to 60 weeks ("Enlisted Jobs", 2010). The Army is allocated a budget of 30.64 billion dollars annually to support the enlisted force. In order to maintain this enlisted force, a very large and complex simulation and optimization program is used by the Army G1 to forecast the planning and allocation of MOS by grade over a seven-year planning horizon.

B. BACKGROUND

Army analysts working at the Deputy Chief of Staff, G1 (Personnel) are responsible for effectively managing the Army. This is accomplished with the aid of multiple mathematical models on the Army's personnel projections that

are used to ensure the Army has Soldiers with needed specialties and seniority (Cashbaugh, Hall, Kwinn, Sriver, & Womer, 2007). The Army G3 (Operations and Plans) and the Army G1 work together to create the Personnel Management Authorization Document (PMAD) that meets the requirements for manning the force (Cashbaugh et al., 2007). The PMAD states the personnel authorizations for all units within the Army. These authorizations ensure the Army conforms to law and policy for the next seven years as set forth by Congress.

The PMAD is used to create a distribution plan and estimate the cost of the manpower program for the Army. In order to achieve this forecast, the Army uses an integrated suite of forecasting models know as the Active Army Strength Forecaster (A2SF). The A2SF consists of three individual models that are dependent upon each other to make an accurate overall forecast. The three models are the Individual Accounts (IA) model, the Enlisted Grade (EG) model, and the Enlisted Specialty (ES) model. Figure 1 provides a graphical depiction of the A2SF.

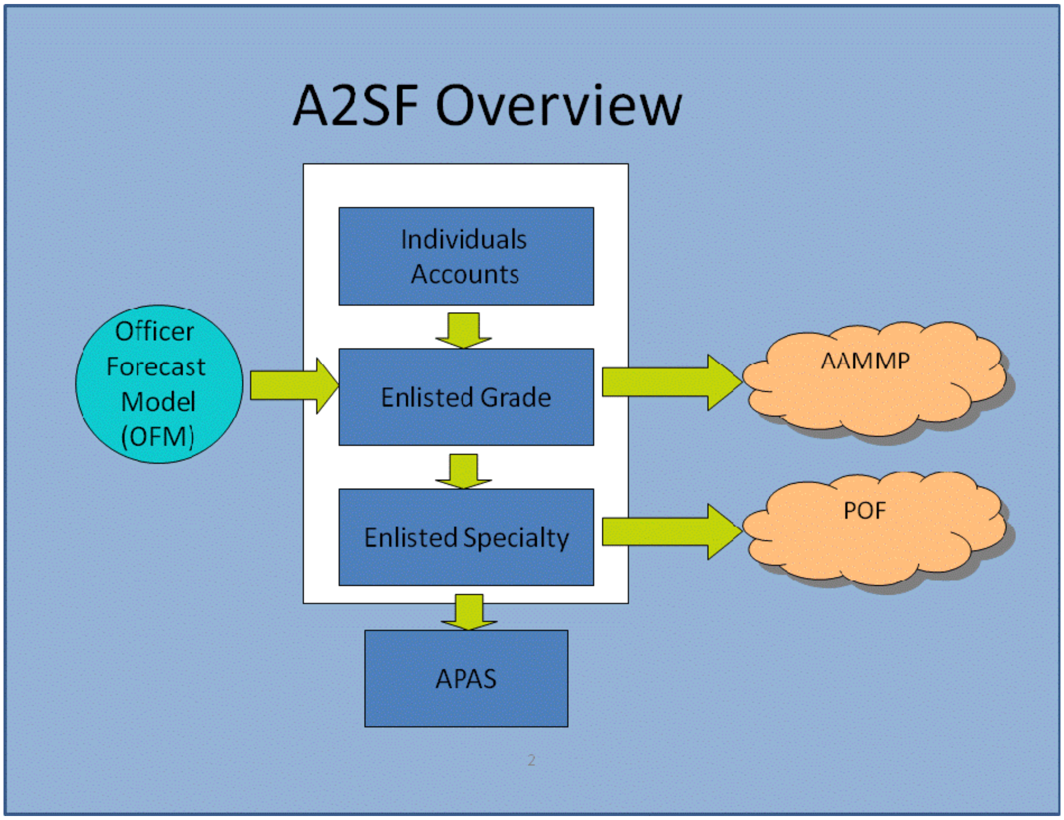

Figure 1. A2SF Model Overview

1. A2SF Description

The Individual Accounts (IA) model is used to forecasts Soldiers that are not permanently assigned to a unit. These are Soldiers that are in transition from one unit to another, medical holding, or are in school. These groups of Soldiers are commonly lumped together into what is reported as Trainees, Transients, Holdees, and Students (TTHS) in Army reports. The IA is important because the Soldiers currently being tracked in this model are not counted against the active Army’s end strength (Cashbaugh et al., 2007).

The IA model calculates transitional probabilities for Soldiers moving into and out of the IA model for up to 84 months in 24 sub-categories of individuals based on historical data (Cashbaugh et al., 2007). The results of the IA model, specifically the probabilities it generates, are then fed into the Enlisted Grade (EG) Model.

The EG model is used to forecast the total number of Soldiers in the Army by pay grade. This model is combined with the Officer Forecast Model (OFM) to produce a forecast for strength, accessions, losses, and promotions. This forecast is based on grade, gender, months of service, and terms of service of the Soldiers currently being modeled (Cashbaugh et al., 2007). Results from the EG are used for creating the Active Army Military Manpower Program (AAMMP) and the President’s Budget. These results become a series of constraints for the Enlisted Specialty (ES) model to allocate personnel against.

The ES model is comprised of an optimization and simulation that forecast the Army’s enlisted manpower program by Military Occupational Specialty (MOS) and grade across a seven year planning horizon. The ES model is used to study both force-structure changes and policy implications for the United States Army (Cashbaugh et al., 2007). A single run of the ES model results in projected manpower inventory (by month, skill, and grade). This data is processed and becomes input for the Analyst Projection Assistance System (APAS) in Human Resources Command (HRC) to be used for personnel distribution planning.

The APAS planning includes setting promotion rates for enlisted Soldiers, influencing the Army Training

Requirements and Resources System (ATRRS), and directing the accession mission for new and prior service Soldiers entering the Army.

The ES model, the third component in the A2SF suite, is the focus of this thesis and is discussed in further detail in the next section.

2. Enlisted Specialty Model

The ES model is designed to forecast strength, gain, losses, promotions, training graduates, reclassifications, and conversions for enlisted Soldiers. The model allows further subdividing of certain specialties to incorporate more skill identifiers, such as language proficiency. Since the ES model aligns operating strength with authorizations at individual MOS and grade level it is more specific in its allocation of Soldiers than the EG model. As noted in Chapter I.A.1, the EG model only evaluates, or takes into account, Soldiers by their pay grade.

The ES model simulates the predicted flow of Army personnel on a monthly basis using historical data to determine input rates and factors for future transactions. The personnel inventory is comprised of two components, the individual account, which is made up of Soldiers not available for operational assignments due to training, transitions, holdee status or student status, and the operating strength account, which is made up of Soldiers available for assignment against an authorization.

The optimization portion of the model strives to minimize the absolute deviation between the operating strength portion of the personnel inventory and the

authorizations to best meet the force structure requirements while satisfying all of the constraints.

Objective function coefficients set penalties and rewards for the optimization. By adjusting the penalties and rewards, the user can focus the optimization on certain aspects that the user wants to investigate to see impacts of future decisions. Examples of these rewards and penalties include increasing the penalties for branch transfers to investigate the effects of limiting Soldiers abilities to switch from one MOS to another and how that affects basic training requirements to fill a needed MOS. Additionally, rewards to retirement losses can be used to investigate the effects of downsizing the senior Non-Commissioned Officer ranks.

The ES model is focused on individual MOSs, and it uses the pay grade requirement computed in the EG model as a constraint, but it is able to allocate changes to each MOS to achieve its various goals (strength, gain, losses, promotions, training graduates, reclassifications, and conversions) in assigning Soldiers. When the ES model is complete, it aligns the projected forces with the authorizations due to the various constraints (training seats, promotion rates, force structure changes etc.) as closely as possible. The difference in the projected force from the authorizations is referred to as a deviation.

The deviation between the authorized number of Soldiers and what the model is able to allocate becomes a source of friction in force management and the Army G1 seeks ways to minimize this deviation. The deviation becomes a bench mark to see how well the force structure can be allocated. If

over the seven year planning horizon the model stays closely aligned to the Authorizations, then the Operating Strength Deviation (OSD) will stay relatively close to zero. As the OSD increases the gap between on-hand Soldiers and authorizations is increased, and there is either a shortage or excess of Soldiers in certain MOSs.

3. Enlisted Specialty Model Specifications

The ES model was originally built to replace the Military Occupational Specialty Level System (MOSLS) that was developed in the early 1970s by General Research Corporation, which is now a part of AT&T Government Solutions (Hall, 2004). MOSLS was an earlier generation of the current ES model and had essentially the same mission to balance MOSs and grade level requirements with the available population of Soldiers. AT&T Government Solutions developed the ES model for the G1 and continues to provide direct support to the Army G1 when they are exercising the model.

A typical model instances consists of approximately 860,000 variables with 225,000 constraints (Interview with J. Vergilio, on December 01, 2009 at AT&T Government Solutions, Vienna Virginia). Several iterations of the model are run in order to converge to a feasible solution. The optimizer prescribes the promotions, accessions and reclassifications rates to minimize the OSD while still staying within the constraints (Hall, 2004). The simulator is used to adjust for changes in behavior due to the different promotion, accession, and reclassification programs.

In the first iteration, the simulator estimates the number of transactions necessary to meet the Force Structure objective. In order to do this, the simulator models Soldiers loss from war-fighting units to training. It then corrects the data base, for any MOSs that are being deleted or converted to other MOSs. The simulator then simulates Soldiers that are reclassifying from one MOS to another and losses or Soldiers getting out of the Army. The simulator then figures out the percentage of Soldiers being promoted from one rank to another, the gains the Army will have in the war fighting units from training and from the THS program, and then finally ages everyone modeled in the simulation to the next month. This process is depicted in Figure 2.

Figure 2.   Simulation Overview

The simulator executes each of the steps in Figure 2 in a linear order for each projection month of the seven year forecast. The ES program's simulator predicted transactions then become bounds on the optimizer, which is run for 15 iterations. The first 12 iterations of the optimizer are solved with CPLEX using the barrier quadratic method and the last three iterations are solved with mixed integer programming using a barrier plus crossover program. The CPLEX barrier quadratic method is designed to solve linear and quadratic problems. The method calculates the feasible region of a problem and adds a very large (near infinity) penalty term to the calculated solution if that solution moves outside the feasible region of the problem. This design ensures that a minimization problem stays within the feasible region. A Mixed-Integer Program (MIP) is the minimization (or maximization) of a linear function subject to linear constraints where some of the decision variables are constrained to have only integer values (CPLEX, 2010).

The final iteration of the optimizer produces a forecast that is an integer value and resolves any final discrepancies between the ES and EG projections. As the program is currently configured, it takes approximately four hours to determine rates and factors and then 17 hours for the model to process through all 15 simulation and optimizations iterations using the AT&T Government Solutions' servers and database.

C. PROBLEM STATEMENT

The Army manpower program is a 30.64 billion dollar annual investment. Its size, diversity in the skills it needs, the cost in terms of dollars, and years to produce

skilled Soldiers requires that the manpower program be closely managed. Currently, the ES model is operating and generating feasible solutions to the very complex problem it receives from its A2SF counterparts. The question remains, can a better solution be found than is being generated now?

This thesis uses design and analysis of experiments to study the ES model in an attempt to answer a fundamental question:

- What are the objective function coefficient values that have the greatest effect on lowering the absolute deviation between the operating strength and the authorizations?

The answer to this question gains insights that generate better solutions for matching personnel to authorizations and lower the OSD. This helps ensure the model results indicate the Army has the right number of Soldiers with the correct skill sets and rank to manage the Army.

D. THESIS OUTLINE

Chapter II gives an accounting of the objectives of this thesis and why it is important. This chapter also discusses the methodology of Design of Experiments (DOX), including the screening experiments and design augmentation along with the scope, limitations, and assumptions used in this thesis. Chapter III discusses the inputs, outputs, and the design matrices used in the course of experimentation. Chapter IV discusses the results of the design matrices used and the mathematical formulation to predict the outcome and recommended changes to the current coefficient settings. Chapter V discusses the conclusions and recommendations for future research.

II. METHODOLOGY

A. OBJECTIVES

This thesis explores the ES model’s coefficients in an attempt to study the impact on OSD. This involves determining how sensitive results of the model (OSD values) are to changes in the objective function coefficients. The primary means to examine the ES model is through design of experiments. The ultimate goal of this research is to see how the coefficients in the objective function of the ES model can be better manipulated to bring the OSD closer in line with the authorizations.

The information obtained through this research will subsequently affect the recommended personnel distribution plan for the active Army. A one percent change in the overall efficiency of the program could lead to an annual savings of 300 million dollars. By examining the ES model, and bringing the enlisted manpower program closer to its authorized levels, there is a potential decrease in the excess or shortage amounts of Soldiers in the United States Army by MOS and grade.

B. METHDOLOGY OVERVIEW

Design of Experiment (DOX) is a systematic way of exploring a problem where variations are present. The experiments are designed so an analyst can conduct simultaneous examination of multiple factors and explore these factors and their relationship to output responses. This allows researchers to identify, compare, and contrast

current values while minimizing the number of experiments that need to be conducted. Practicing good experimental design techniques allows for the most cost-effective (in terms of computer processing time, money, etc.) collection of data for future analysis. DOX principles (Montgomery, 2009) will guide the execution of experiments on the ES model and ensure a comprehensive exploration of the problem space and efficient use of computer processing resources. The DOX will dictate what design factor values are varied during multiple experiments, so that the data is capable of providing valuable insight into how the coefficient inputs can reduce the OSD.

1. Screening Experiments

When an experiment is very large with multiple factors, it is often appropriate for a screening experiment (or characterization experiment) to be conducted (Montgomery, 2009). The screening experiments allow researchers to learn which of the factors being tested are of importance with respect to a response variable of interest. In order to accomplish this screening, an experiment is designed that allows us to estimate the magnitude and direction of the factor effects (such as main effects and two factor interactions) in relation to the response variable. The subset of factors that represented the greatest amount of information about the response variable can then be further analyzed. By having a fewer number of factors more concentrated, experiments can be conducted on only those factors that have a substantial impact on the response variable in question. The process of screening is

especially important in studying models that take a long time to run, such as the case of the ES model, which takes 21 hours to complete.

2. Design Augmentation

In some situations, it is useful and more economical to augment an existing design rather than to perform a completely new experiment. This augmentation is very useful when the optimum factor settings for an experiment are within the original experimental region. This is because the design can be augmented around the already established response surface. Design augmentation can also be used when the initial experiment cannot distinguish between confounded or multiple significant effects. The design augmentation is able to break certain confounded strings from an original experiment. Design augmentation can also be used when additional experimentation is expensive or too lengthy to conduct. Augmentation allows the reuse of information from an initial screening experiment; therefore, time and energy does not have to be wasted from the previous experiments conducted.

C. SCOPE, LIMITATIONS, AND MANPOWER DATA ASSUMPTIONS

1. Scope

The scope of this project is limited to the examination of the model’s objective function coefficient data inputs. Specifically, this design of experiment will explore the 52 coefficients involving grade, non-network constraint, and

objective function arc coefficients in the ES model objective function. These coefficients have a variety of possible input ranges.

The 52 objective function coefficients are shown in the Appendix (acronym definition provided on page xiii). Additionally, their value ranges and current default setting are also provided. The possible minimum and maximum ranges for the coefficients is determined from the Graphical User Interface. Experimentation on the range of entries that allow the optimization and simulation to converge is limited and explained in Chapter III of this thesis.

2. Limitations

Given the immense size of the ES program, this thesis only looks at the September 2009 data set and objective function coefficients of the ES model. This thesis holds the other inputs to the model constant and does not look at variations of those inputs. The internal workings of the ES program's optimization and simulation programming are not changed or modified in the course of this study. Furthermore, the priority of transactions or a cost-benefit analysis of decisions made in terms of OSD are not examined.

3. Assumptions

The thesis is based on the assumption that the PMAD the G3 created will remain constant for all seven years of the forecast. Additionally, it is assumed that the historical data and distributions set forth in the simulation are indicative of future events.

III. DESIGN OF EXPERIMENTS: MATRIX AND RESULTS

In this chapter, we discuss the inputs to the model along with limitations those inputs have. The meaning behind the output is examined in this chapter along with a discussion about the Plackett-Burman experimental design matrix.

A. INPUTS AND OUTPUTS

1. Inputs

The allowable entries for each of the coefficients from the Graphical User Interface are quite vast in the range of numbers that could be entered. A few initial runs of the ES program were designed to test and determine if the program was able to converge on an answer when given the extreme values. In all test cases where the extreme values were used, the program was unable to converge on an answer. Given this, the next step was to determine the range of values to test in the model for each factor that would allow the program to converge on an answer. AT&T Government Solutions provided some insight into acceptable ranges that allow the model to converge. Specifically, they stated:

1) If promotion factor coefficients are set to positive values, the model may be unstable.
2) strength factors should not be set to negative numbers.
3) If the MOSS Shred coefficient and/or SL1 constraints coefficient are set to zero, the model is unstable.

4) Non-zero values for NCO Constraint increase the model size.

5) If MOS Deletions is not set to zero the model has great trouble converging to an answer.

6) Demotion, loss (PML) and percent bound on pool flows coefficients are no longer used in the model and have no effect on the model.

Given the input from AT&T, NCO constraint, MOS deletions, demotion, loss (PML) and percent bound on pool flows coefficient values and not be changed during testing in this thesis. Several additional test runs of extreme values for each coefficient were conducted. At the conclusion of those tests it is determined that the range of possible input values for most of the coefficients are limited to +/- 20% of the possible input range centered around the default value.

Table 1 depicts the minimum and maximum ranges that are used in the course of research along with the current default values used in the model. The values in Table 1 represent the actual number ranges for values entered during a single run of the ES model. During the analysis, these number ranges are all converted into coded units [-1, 1] in order to standardize all model coefficient values.

Grade Coefficients	Min Range	Max Range	Default Value
Promotion Factors E3	-200	-1	-120
Promotion Factors E4	-30	-1	-4
Promotion Factors E5	-30	-1	-4
Promotion Factors E6	-30	-1	-4
Promotion Factors E7	-30	-1	-4
Promotion Factors E8	-30	-1	-4
Promotion Factors E9	-30	-1	-4
Reclass Factors E3	3000	7000	5000
Reclass Factors E4	1	400	5000
Reclass Factors E5	1	400	200
Reclass Factors E6	1	400	200
Reclass Factors E7	1	400	200
Reclass Factors E8	1	400	200
Reclass Factors E9	1	400	200
Strength Factors E3	0	200	0
Strength Factors E4	1	4000	2000
Strength Factors E5	1000	5000	3000
Strength Factors E6	2000	6000	4000
Strength Factors E7	3000	7000	5000
Strength Factors E8	4000	8000	6000
Strength Factors E9	5000	9000	7000
Target Factors E3	0.01	1	0.1
Target Factors E4	0.01	1	0.1
Target Factors E5	0.01	1	1
Target Factors E6	0.01	1	1
Target Factors E7	0.01	1	1
Target Factors E8	0.01	1	1
Target Factors E9	0.01	1	1

Non-Network Constraint Coefficients	Min Range	Max Range	Default Value
MOSS Shred Target	0.01	0.32	0.13
NCO Constraint	0	0	0
SL1 Constraint	0.1	0.5	0.3

Objective Function Arc Coefficients	Min Range	Max Range	Default Value
Conversion	-9500	-5500	-7500
MOS Deletion	0	0	0
Demotions	-6000	-6000	-6000
LOSSES (ETS)	-9999	-8000	-9999
LOSSES (Other)	-9999	-8000	-9999
LOSSES (PML)	-50	-50	-50
LOSSES (Retirement)	-9999	-8000	-9999
LOSSES (Training)	-9999	-8000	-9999
Promotion (VBU)	-7000	-3000	-5000
Percent Bound on Pool Flows	100	100	100
Reclassification (Mandatory)	-9999	-8000	-9999
Reclassification (Reenlistee)	-9999	-8000	-9999
Reclassification (Voluntary)	0	100	1
Same-Grade Reclassifications	0	100	10
THS	-9100	-5100	-7100
BCT Training	0	65	31
NPS Without Training	1200	5200	3200
OSUT Training	0	65	33
PS with Training	0	65	34
PS Without Training	1500	5500	3500
Training Deletions to Pools	0	80	40

Table 1. 52 Objective Function Coefficients with Experiment and Default Values

2. Output

The response variable for this design of experiment is the Operating Strength Deviation (OSD) or the sum of the absolute deviations between the authorizations and allocated number of Soldiers by month for the projected seven years. The range for the OSD is zero, indicating perfect alignment between authorizations and Soldiers available, to 38 million, indicating a complete misalignment for the entire seven year projection.

B. STATISTICAL ANALYSIS SOFTWARE

When the ES program is completed with its run, it produces five output Comma Separated Values (CSV) files. These files vary in size but contain all the output information from the ES model run. Programming code for Statistical Analysis Software (SAS) was written to combine the five CSV files into one complete CSV file. From this one file, the OSD is computed.

C. PLACKETT-BURMAN EXPERIMENTAL DESIGN MATRIX

The Plackett-Burman design is a widely used screening design for experiments that require a large number of factors. The Plackett-Burman design, developed by Plackett and Burman (1946), is a non-regular factorial design with a low number of experiments. A non-regular design is one that involves partially confounded factors. Thus, main effects are partially confounded with higher order interactions and non-linear terms. However, higher order terms are not expected to have large contributions or dominate the results. Additionally, in the screening experiment, the

main effects and two factor interactions are of most interest. For examining the ES model a Plackett-Burman model is used to determine which of the 52 Objective Coefficient Variables will be important in terms of the response variable OSD.

The Plackett-Burman model has a few unique characteristics to it. It can be used when the sample size is a multiple of four rather than a power of two as seen in other fractional factorial designs (Montgomery, 2009). The main effects of the design are orthogonal and two-factor interactions are only partially confounded with the main effects. The max correlation between pairs of two-factor interactions is +/- 1/3.

A Plackett-Burman design is created by establishing a base design consisting of a Hadamard matrix. The Hadamard matrix is a square matrix with entries that are either -1 or +1 (representing the low and high coded coefficient values) and has all the rows mutually orthogonal to each other. Once that is complete, the columns in the matrix can be manipulated so that in the second column the last term (either -1 or +1) is moved to the top position and all other terms are shifted down one row. The third column is created by taking the last two terms and moving them to the top position and shifting all the other terms down two rows and so on until you have manipulated all the columns in the matrix. Once this is complete, a row of either -1 or +1 is added to ensure there is an equal number of -1’s and +1’s in the column to the top of the matrix.

A portion of a Plackett-Burman screening with 52 factors in coded units is shown in Table 2.

	X1	X2	X3	…….	X49	X50	X51	X52	Y
1	-1	-1	-1		-1	-1	-1	-1	.
2	-1	-1	-1		1	1	1	1	.
3	-1	-1	1		-1	1	-1	1	.
4	-1	-1	1		1	-1	1	-1	.
5	-1	-1	1		1	1	1	-1	.
6	-1	-1	1		-1	-1	-1	1	.
7	-1	-1	1		1	1	-1	-1	.
……									
49	1	1	1		1	1	1	-1	.
50	1	1	1		-1	-1	-1	1	.
51	1	1	1		-1	-1	-1	1	.
52	1	1	1		1	1	1	-1	.
53	1	1	1		1	-1	-1	-1	.
54	1	1	1		-1	1	1	1	.
55	1	1	1		-1	1	1	-1	.
56	1	1	1		1	-1	-1	1	.

Table 2. Plackett-Burman Screening Design Matrix

Coding the units -1, 1 allows the researcher to directly compare magnitude and direction of effects on a unitless scale.

The Plackett-Burman design in engineering units for the ES model is depicted in Table 3.

	Promotion Factors E3	Promotion Factors E4	Promotion Factors E5	.....	PS with Training	PS Without Training	Training Deletions to Pools	OSD Response Variable
1	-200	-30	-30		0	1500	0	.
2	-200	-30	-30		65	5500	80	.
3	-200	-30	-1		65	1500	80	.
4	-200	-30	-1		0	5500	0	.
5	-200	-30	-1		65	5500	0	.
6	-200	-30	-1		0	1500	80	.
7	-200	-30	-1		65	1500	0	.
....								
49	-1	-1	-1		65	5500	0	.
50	-1	-1	-1		0	1500	80	.
51	-1	-1	-1		0	1500	80	.
52	-1	-1	-1		65	5500	0	.
53	-1	-1	-1		0	1500	0	.
54	-1	-1	-1		65	5500	80	.
55	-1	-1	-1		65	5500	0	.
56	-1	-1	-1		0	1500	80	.
Average	-100	-15	-15		33	3500	40	.

Table 3. Plackett-Burman Screening Design Matrix with Engineering Units

The initial screening of the 52 coefficients in the Plackett-Burman design of experiments requires 56 runs. These 56 runs provide insight into what factors are important in relation to the OSD and which factors require more testing. Note, that a run is equivalent to a single experiment, meaning the ES model is programmed and executed with the values prescribed by a single row in the design matrix (Table 3).

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IV. ANALYSIS

This chapter discusses the results of the ES model experimentation. The prediction equation for determining the OSD is highlighted along with recommended changes to the objective function coefficients.

A. ENLISTED SPECIALTY MODEL AUGMENTATION

In order to conduct testing of the ES model, AT&T Government Solutions designed a reduced model for work on this thesis. This reduced model consisted of the September 2009 data set and pre-calculated the rates and factors for the previous four years. With this model, the Simulation Experiments & Efficient Design (SEED) Center at the Naval Postgraduate School were able to deploy the model on their cluster of computers. With use of the cluster of computers, the reduced model was able to run five separate design points every 8-10 hours. Without this reduced model and the SEED center, work on this thesis would have been limited to one design point calculated every 21 hours.

B. SCREEING DESIGN RESULTS

1. Testing Standard Deviation

Standard deviation is a measurement of the variability or the variation from the mean in an experiment. A low standard deviation means the data tends to be very close to the mean. The ES program uses a six digit random number generator that changes the value of the random seed in both the simulator and optimizer and creates variability in the

program. Sixteen experiments were conducted using the default coefficient settings to test the standard deviation of the model. Figure 3 depicts a cumulative graph of the empirical standard deviation from the 16 experiments conducted and shows that the standard deviation converges to a value of 6,000.

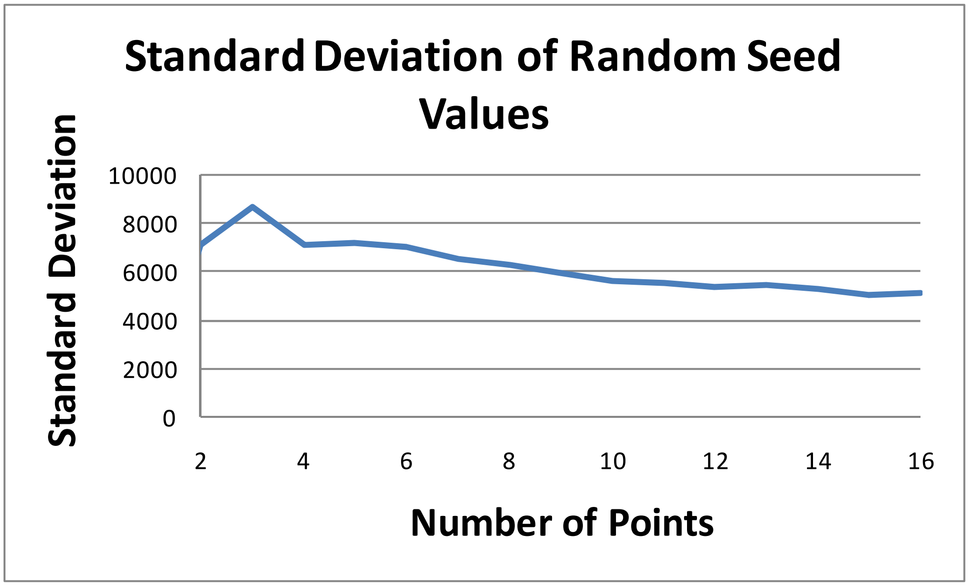

Figure 3. Standard Deviation of Random Seed Values

In the experiments, the standard deviation was calculated to be 5,666. When compared to an OSD average of approximately 3.3 million, the standard deviation caused by the random number accounts for less than 0.18% variation in the model’s overall OSD. This low-standard deviation indicates that the deviation caused by the random number generator is very close to the mean.

2. Screening Experiment Results from Plackett-Burman

The results from the Plackett-Burman screening experiments had a wide range of OSD outcomes. For

calculating a baseline to compare these results, the default coefficient values were used. When the default values are entered and the program is executed, the OSD is 3,306,497. In the 56 Plackett-Burman experiments, the minimum OSD achieved was 2,834,534 and the maximum OSD was 4,859,177. Normalizing each experiment in relation to the default OSD makes the results easier to understand. The percentage of change from each experiment is shown in Figure 4. As illustrated, there is quite a difference in the percentage of change from one experiment to another with six experiments resulting in a lower OSD than using the default coefficient values.

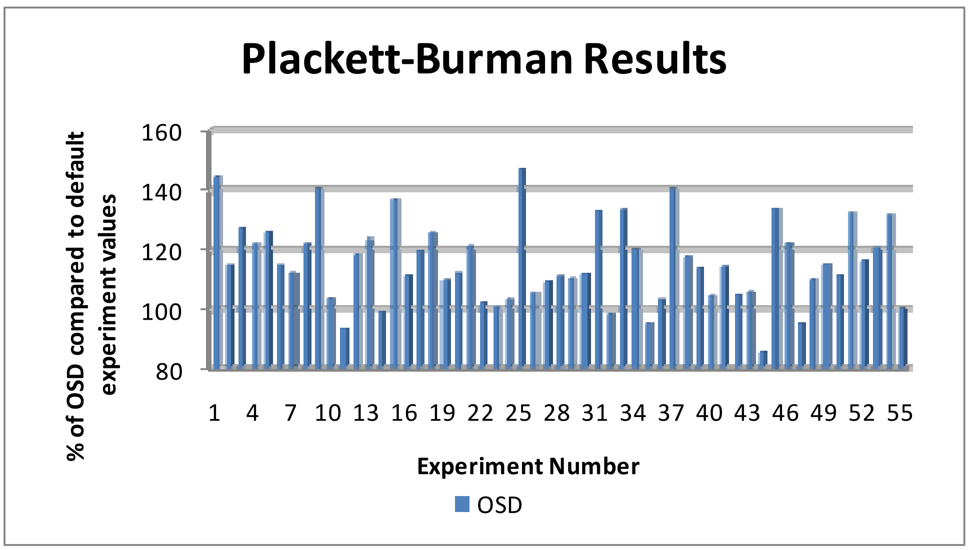

Figure 4. Plackett-Burman OSD Percentage Results

The results of these experiments were examined using JMP® software (JMP®, 2010). Stepwise linear regression was used to find statistically important factors to predict the OSD. All 52 coefficient main effects and all possible two factor combinations (also known as two factor interactions

or 2FI) were added as potential effects. This results in 1,431 terms that were analyzed to look for statistical significance.

Note, that this is far more terms than design points initially. The Plackett Burman design is irregular, which means correlations are present in the terms and significant terms must be deconfounded in the additional runs of the model. The irregular design allows the use of stepwise regression for this large amount of terms.

The theory behind mixed forward and backwards stepwise linear regression is to start with no variables in a model and try out the variables one by one and including them, if they have statistically significant importance. After a new variable is added to the model, a test is made to check if some of the variables already added can be deleted without dramatically increasing the residual sum of squares. This continues until all the possible variables are analyzed.

Once the stepwise regression results were completed, least squares regression was used to build a model to predict the OSD outcome. The least squared regression models developed in this thesis always had far fewer terms than design points.

Least squares regression is designed to build a mathematical model that fits a line using the factors determined to be of importance (through stepwise linear regression). The equation for the line is designed to come as close as possible to the observed points in the data. The closer the line comes to the observed points; the lower the sum of the square errors is between points and the better the model.

In order to measure how accurate a least squares regression prediction is to observed data, R^2 and adjusted R^2 are used. R^2 is the proportion of variability in a data set that is accounted for by the statistical model. The values of R^2 can vary from 0 to 1, with higher values being more desirable. The problem with R^2 is that the number can be artificially inflated by adding more terms to the equation. Adjusted R^2, which adjusts for the number of terms in a model can account for this artificial inflation. The adjusted R^2 value increases only if the new term improves the model by reducing the residual mean square [Montgomery, Peck, & Vining, 2006]. The results from the screening experiments are presented in Table 4 (Summary of Fit) and Table 5 (Significant Factors).

Summary of Fit	
RSquare	0.988636
RSquare Adj	0.983924

Table 4. JMP® Output of Summary of Fit from Plackett-Burman Experiments

Parameter Estimates	
Term	**Estimate**
Intercept	352091.21
Strength Factors E4	3428.0933
SL1 Constraint	-1130.819
Promotion Factors E5*Promotion Factors E6	-2845.178
Promotion Factors E8*Target Factors E4	5925.8127
Reclass Factors E5*Strength Factors E5	2284.1627
Reclass Factors E6*Target Factors E7	-2795.389
Reclass Factors E6*SL1 Constraint	1341.4701
Reclass Factors E9*Strength Factors E8	-2333.568
Strength Factors E3*SL1 Constraint	-3604.157
Strength Factors E4*LOSSES (ETS)	-2307.061
Strength Factors E4*NPS Without Training	-2806.16
Strength Factors E5*PS Without Training	-2011.372
Strength Factors E7*Target Factors E9	17766.789
Strength Factors E8*PS Without Training	4506.6355
Demotions*Reclassification (Reenlistee)	1662.5679
LOSSES (Retirement)*NPS Without Training	1189.8346
BCT Training*OSUT Training	9892.3711

Table 5. JMP® Output of Significant Factors from Plackett-Burman Experiments

The "Term" column in Table 5 shows which coefficient factors (linear or interaction) from the ES model were determined to be of importance for the least squares model. The "Estimate" column contains the linear model coefficient values. For example, increasing the SL1 constraint by a single unit decreases the OSD by approximately 1,131. This is due to the fact that increasing SL1 constraint means that a higher priority is placed on skill level 1 Soldiers. Notice that there are a large number of two-factor interactions present. By design, these interactions have partial confounding with other two factor interactions.

Therefore, additional experimentation is necessary to estimate these effects and determine whether they are truly significant. The next section discusses the additional experimental trials.

C. ADDITIONAL EXPERIMENTS AND MODEL REFINEMENT

1. D-Optimal Latin Hypercube

Once the significant factors were determined from the Plakett-Burman, a D-Optimal Latin Hypercube design (D-Opt LHD) was conducted. The D-Opt LHD was only used on the top nine factors from the previous experiment and holding the other 43 coefficients at their default values.

A D-Opt LHD (Jones, Johnson, & Montgomery, 2010) is a space-filling design where the design points are nearly orthogonal (or perpendicular) to each other. The D-Opt LHD is a flexible experimental design technique that provides a compromise between a D-optimal design and a Latin Hypercube design (LHD). A D-optimal design is one that minimizes the joint confidence region around the unknown model coefficients. The D-optimal design is only optimal with respect to the linear model specified. The LHD is a space-filling design that attempts to sample over many portions within the design region. Results from the Plackett-Burman presented in the last section guided the specification of the *a priori* model used to generate the D-Opt LHD. The terms that were found to be significant were included as terms used for optimizing the experimental design.

In the previous section, it was mentioned that some of the significant terms could have partial confounding due to

the initial choice of the Plackett-Burman design. By specifying the fitted model in the creation of the D-Opt LHD confounding was removed from the significant terms in the model, and the resulting design matrix was very nearly orthogonal. The maximum correlation between any potentially significant factors was below 0.1.

A D-Opt LHD with 20 experiments was generated and run. Once complete, the results of the 20 runs were processed through the SAS code and compared to the default coefficient OSD listed as experiment 21 on the graph (Figure 5).

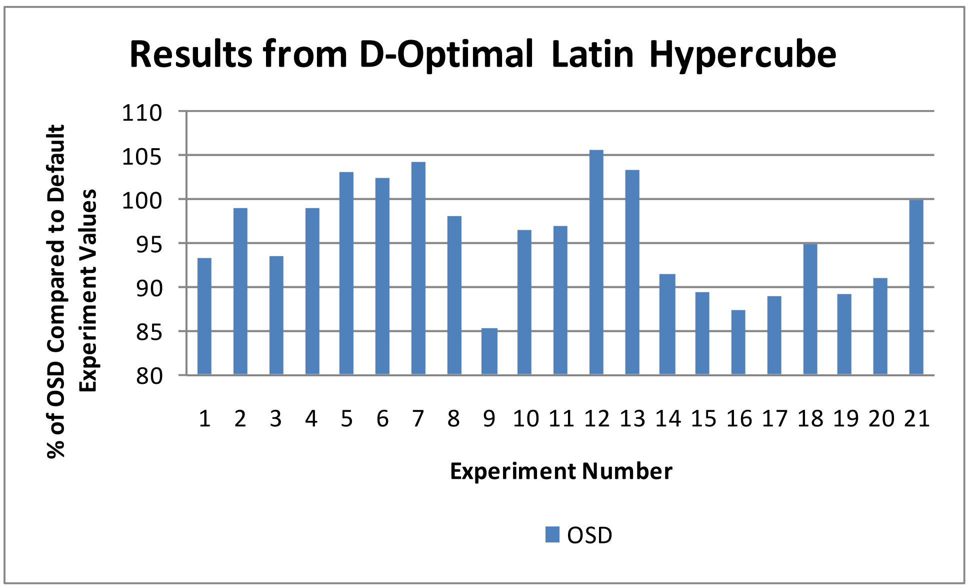

Figure 5. D-Optimal Latin Hypercube OSD Percentage Results

Figure 5 illustrates that by manipulating nine coefficients and holding the rest at their default values, 75% of the OSDs fall below the current default OSD. These results are encouraging and show that these nine coefficients are important and can be used to reduce the overall OSD in future experiments. The R^2 and Adjusted R^2 from the model created based on the combined data from the

Plackett-Burman and D-Optimal experiments are shown in Table 6, and the significant factors are shown in Table 7.

Summary of Fit	
RSquare	0.997783
RSquare Adj	0.995987

Table 6. JMP® Output of Summary of Fit from D-Optimal Experiments

Parameter Estimates

Term	Estimate
Intercept	3025495
Strength Factors E4	-157729 5
Target Factors E4	-78539 4
SL1 Constraint	111753.04
BCT Training	-80914.72
OSUT Training	-86611.91
Promotion Factors E3*Promotion Factors E8	14490.416
Promotion Factors E4*NPS Without Training	-17316.45
Promotion Factors E5*Reclass Factors E9	43755112
Promotion Factors E7*Reclass Factors E6	25798.463
Promotion Factors E8*Target Factors E8	-25673.35
Promotion Factors E8*Same-Grade Reclassifications	-40249.65
Promotion Factors E9*Reclass Factors E4	-37737.25
Reclass Factors E3*Reclass Factors E6	42091.22
Reclass Factors E3*Reclass Factors E8	-46745.88
Reclass Factors E3*Strength Factors E3	61064.105
Reclass Factors E3*Target Factors E9	42427.971
Reclass Factors E4*PS Without Training	-50719.46
Reclass Factors E6*Reclass Factors E8	72177.917
Reclass Factors E6*Reclassification (Reenlistee)	34548.525
Reclass Factors E8*Conversion	28010.759
Strength Factors E3*Reclassification (Reenlistee)	-25926.99
Strength Factors E4*BCT Training	66445.694
Strength Factors E7*Target Factors E9	148466.82
Strength Factors E9*Target Factors E9	156911.85
Target Factors E7*PS with Training	-11260.03
SL1 Constraint*Reclassification (Mandatory)	43816630
LOSSES (Other)*BCT Training	38277.963
Promotion Factors E8*Promotion Factors E8	843613.12
Strength Factors E4*Strength Factors E4	138305.29
Strength Factors E8*Strength Factors E8	-434527 6
Target Factors E4*Target Factors E4	482087.36
Target Factors E9*Target Factors E9	-718729 7
MOSS Shred Target*MOSS Shred Target	244802.16
PS Without Training*PS Without Training	226064.12

Table 7. JMP® Output of Significant Factors from Plackett-Burman and D-Optimal Latin Hypercube Experiments

Once again, the list of significant factors is extensive and further testing is required to see if this list of significant terms can be reduced. The amount of terms that are significant at the 0.05 level indicate possible over-fitting. The problem of over-fitting can be mitigated by manually controlling the stepwise regression. This technique is discussed further in the next section.

2. Results of Design Augmentation

The different experiments conducted provide enough data points to begin formulating a simpler mathematical model that maintains high accuracy and precision for predicting the OSD value.

D. MATHEMATICAL FORMULATION OF PREDICTED ENLISTED SPECIALTY OPERATING STRENGTH DIVIATION

1. Cross Validation

All of the experiments completed were tested to see which coefficients were robust with respect to predictive abilities. The data points were placed into JMP® except for 10 randomly excluded points. Stepwise and least squares regressions were executed and JMP® selected the coefficients and that played a significant role in predicting the OSD. Once that was completed, the mathematical equation obtained was used against the 10 previously excluded points. The predicted values matched up closely to the actual values from the original experiments.

This process was conducted 10 times with 10 points randomly excluded each time with surprising results. In all 10 experiments, the predicted values were very close to the

actual values and the R^2 and adjusted R^2 were 0.993 or better. A few of the most influential terms appeared in most of the models. However, there were a large number of terms with small effects. These terms with small effects tended to change from one fit to the next. In the 10 experiments conducted, a total of 210 different coefficient combinations were used. Among all trials, there were a total of 156 coefficients that were significant at the 0.05% level and yet they only appear in one of the 10 models. It appears the Stepwise regression was adding in too many coefficients causing the model to become over-fit and important terms were becoming diluted and then excluded when they should not have been. Note that this was not due to the main effects correlation structure because the D-optimal design removed significant inter-variable dependencies.

In order to prevent the over fitting problem, only the top 10 significant terms were taken from the stepwise regression and used in the Least Squares regression. Taking only the top 10 coefficients eliminated the problem of over-fitting but still resulted in the R^2 and adjusted R^2 being above the 0.90 level. The predictions from these models were plotted against the actual outcome, and the cross validated predictions were generally within five percent of the original point.

The benefit from limiting the information used from the Stepwise regression was that the coefficients in the model were more similar than before. Whereas before when the model was over-fit the coefficients being used seemed random, now the models being produced are more closely aligned with each other and only a total of 24 different

coefficient combinations are used. Of those 24 coefficient combinations used, four coefficients were present in all 10 of the experiments. One coefficient appeared in nine of the experiments, one coefficient was in seven experiments, and four appeared in five experiments with another four appearing in only three experiments. Two coefficients appeared in two experiments and eight coefficients only appeared in one of the experiments. This is significantly better than before where similarities between models were few and far between. Figure 6 shows the coefficients that appeared in the 10 experiments and their frequency rate.

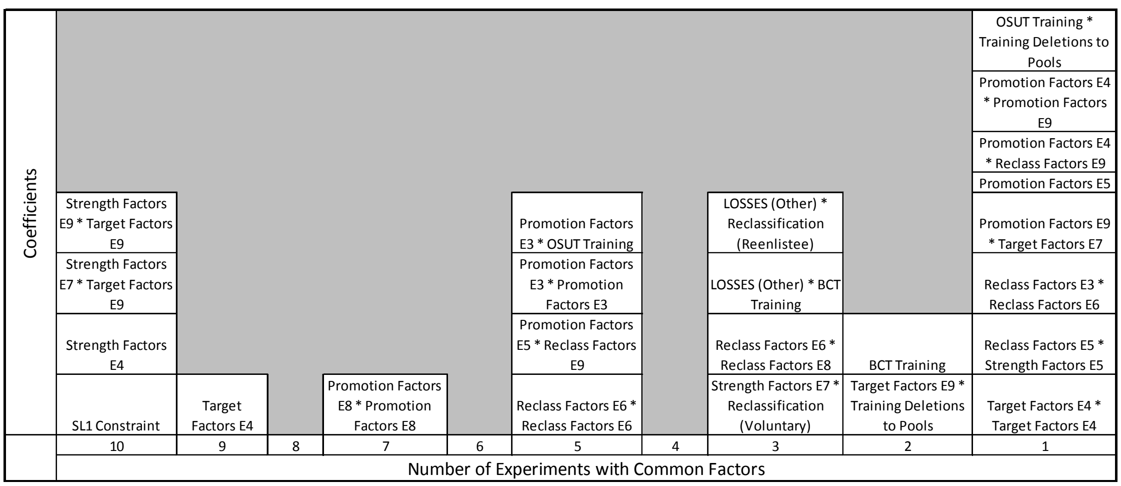

Figure 6. Common Coefficients in 10 Experiments

2. Formulation

Using all design points from the Plakett-Burman and the D-Opt LHD stepwise regression was conducted. The top 10 factors from Stepwise were then used in least squares regression. The OSD prediction equation was calculated to be:

$$OSD = 2965898 + (421044\cdot(\text{Reclass Factors E6})^2) + (213409\cdot\text{Strength Factors E7}\cdot\text{Target Factors E9}) - (189725\cdot\text{Strength Factors E4}) + (193432\cdot\text{Strength Factors E9}\cdot\text{Target Factors E9}) - (117673\cdot\text{Target Factors E4}) + (133118\cdot\text{SL1 Constraint}) + (422804\cdot(\text{Promotion Factors E8})^2) - (92834\cdot\text{Promotion Factors E5}\cdot\text{Reclass Factors E9}) + (74403\cdot\text{LOSSES (Other)}\cdot\text{BCT Training}) + (77190\cdot\text{Promotion Factors E3}\cdot\text{OSUT Training})$$

The predicted OSD values based off the formula above in coded (-1 to 1) values were then plotted against the actual experiments. The maximum average deviation between the actual value and the predicted value was 3.2%. Figure 7 graphically shows the predictions verse the actual calculated values for the OSD.

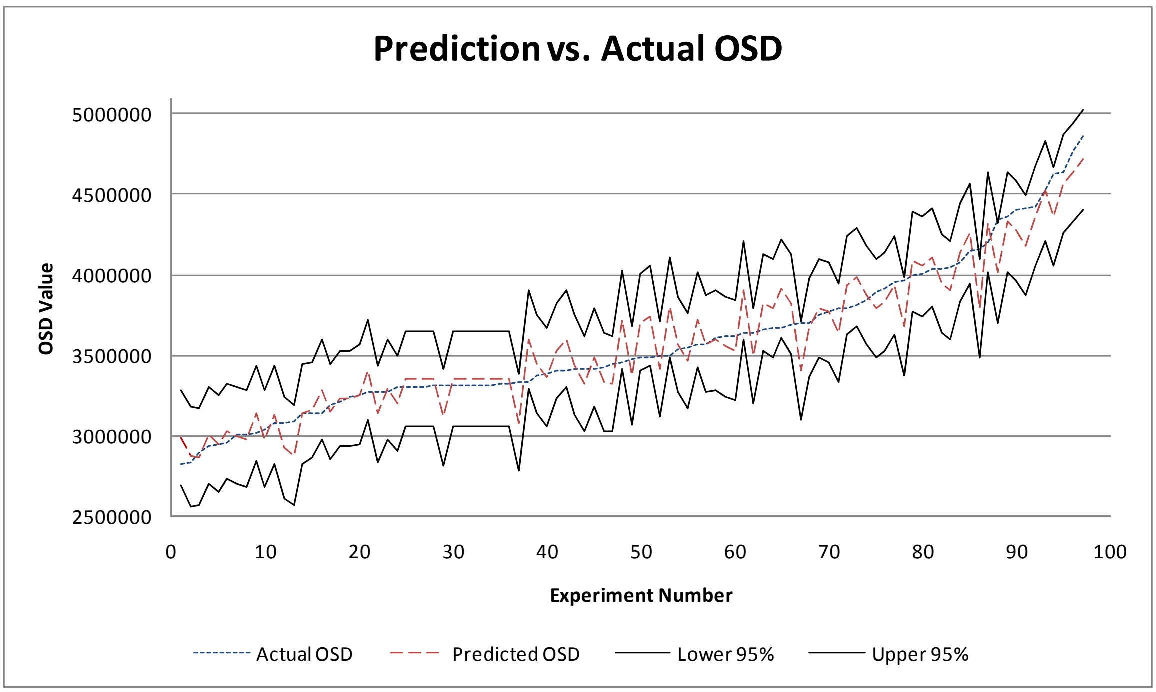

Figure 7. Prediction versus Actual OSD values

By taking the first and second derivatives of the prediction equation, the coded values that are needed to minimize the OSD can be obtained. These coded values are shown in Table 8, along with the corresponding actual units.

		Coded Units			Actual Units		
Strength Factors E4	=	1			4000		
Target Factors E4	=	1			1		
SL1 Constraint	=	-1			0.1		
Reclass Factors E6	=	0			200		
Promotion Factors E8	=	0			-15		
Reclass Factors E9	=	1	or	-1	400	or	1
Promotion Factors E5	=	1		-1	-1		-30
LOSSES (Other)	=	-1	or	1	-9999	or	-8000
BCT Training	=	1		-1	65		0
Promotion Factors E3	=	-1	or	1	-200	or	-1
OSUT Training	=	1		-1	65		0
Strength Factors E7	=	-1		1	3000		7000
Strength Factors E9	=	-1	or	1	5000	or	9000
Target Factors E9	=	1		-1	0.01		-1

Table 8. Prediction Model First and Second Derivatives Results

Using the OSD prediction formula with the specific values listed in Table 8 had mixed results. The model is able to accurately predict points that fall within the cluster of data but when attempting to calculate a point far removed from the cluster the prediction equation cannot extrapolate an accurate answer. This is the result of hidden extrapolation. Coefficient values that result in the lowest OSD are discussed in the next section.

E. COEFFICIENTS THAT MINIMIZE THE ABSOLUTE DEVIATION IN OSD

1. Key Coefficients

In the course of experimentation, there were 13 experiments that resulted in the OSD being at least 10% below the default value of 3,306,497. Of the 13 experiments, 12 share similar values for the coefficients. Given the similarities of these 12 experiments, the coefficient values were averaged and the standard deviation for each coefficient was calculated (results shown in Table 9).

Untested Coefficients	Tested Min/Max Values	Defaults Value	Average	Standard Deviation
NCO Constraint	0/0	0	0	0
MOS Deletion	0/0	0	0	0
Demotions	-6000 / -6000	-6000	-6000	0
LOSSES (PML)	-50/-50	-50	-50	0
Percent Bound on Pool Flows	100/100	100	100	0

Coefficients Requiring No Change	Tested Min/Max Values	Defaults Value	Average	Standard Deviation
Promotion Factors E3	-30/-1	-120	-132	31.90
Promotion Factors E4	-30/-1	-4	-5.58	2.35
Promotion Factors E5	-30/-1	-4	-7.17	7.53
Promotion Factors E6	-30/-1	-4	-4.42	1.08
Promotion Factors E7	-30/-1	-4	-4.67	1.61
Promotion Factors E9	-30/-1	-4	-4.42	1.08
Reclass Factors E3	3000/7000	5000	5083	135.20
Reclass Factors E4	3000/7000	5000	5045	145.76
Reclass Factors E5	1/400	200	196	11.89
Reclass Factors E6	1/400	200	194	13.16
Reclass Factors E7	1/400	200	195	11.98
Reclass Factors E8	1/400	200	211	16.86
Reclass Factors E9	1/400	200	203	85.28
Strength Factors E3	0/200	0	6	12.47
Strength Factors E5	1000/5000	3000	3083	135.20
Strength Factors E6	2000/6000	4000	3917	135.20
Strength Factors E7	3000/7000	5000	4839	1057.65
Strength Factors E8	4000/8000	6000	6223	636.36
Strength Factors E9	5000/9000	7000	6505	756.82
Target Factors E5	.01/1	1	0.97	0.05
Target Factors E6	.01/1	1	0.96	0.08
Target Factors E7	.01/1	1	0.97	0.06
Target Factors E8	.01/1	1	0.97	0.05
MOSS Shred Target	.01/.32	0.13	0.13	0.01
Conversion	-9500/5500	-7500	-7458	148.93
LOSSES (ETS)	-9999/-8000	-9999	-9864	199.95
LOSSES (Other)	-9999/8000	-9999	-9947	112.33
LOSSES (Retirement)	-9999/8000	-9999	-9872	188.22
LOSSES (Training)	-9999/8000	-9999	-9873	186.72
Promotion (VBU)	-7000/-3000	-5000	-4955	145.76
Reclassification (Mandatory)	-9999/-8000	-9999	-9880	178.27
Reclassification (Reenlistee)	-9999/-8000	-9999	-9858	209.11
Reclassification (Voluntary)	0/100	1	4.25	6.43
Same-Grade Reclassifications	0/100	10	11.75	3.84
THS	-9100/-5100	-7100	-7017	135.20
NPS Without Training	1200/5200	3200	3294	145.76
PS with Training	0/65	34	32	2.57
PS Without Training	1500/5500	3500	3838	586.69
Training Deletions to Pools	0/80	40	39	2.57

Recommended Coefficients Change	Tested Min/Max Values	Default Value	Average	Standard Deviation	% Change from Default
Promotion Factors E8	-30/-1	-4	-15	4.11	-273.2
Strength Factors E4	1/4000	2000	2993	622.95	49.7
Target Factors E3	.01/1	0.10	0.16	0.09	59.2
Target Factors E4	.01/1	0.10	0.72	0.19	617.4
Target Factors E9	.01/1	1.00	0.72	0.18	-27.9
SL1 Constraint	.1/.5	0.30	0.25	0.08	-16.9
BCT Training	0/65	31	44	13.65	41.1
OSUT Training	0/65	33	41	15.43	23.3

Table 9. Coefficient Results

Of the 52 coefficients, 39 coefficients had an average that was very close to their default and five were never changed. There are, however, eight coefficients that have an average value that was significantly different from their default value. The standard deviation for these eight coefficients is relatively small, and so one last experiment was conducted to test these eight coefficients to ensure the OSD significantly decreased from the default values. The last experiment using these eight new values was conducted and resulted in an OSD of 2,824,303, which is 85.4% of the default OSD.

2. Interpreting the Results

Understanding the eight coefficients that reduce the OSD can shed light on how the simulation and optimization programs run in the ES model.

Promotion Factors E8: Decreasing the default value from -4 to -15 increases the reward in the optimization program for assigning Soldiers to authorized positions. It is unclear exactly how this increased reward is affecting the model and further study could be devoted to this in follow-on research.

Strength Factors E4: The Strength Factors coefficients are designed to preferentially fill the higher ranks of each MOS before the lower ranks. By increasing the penalty from 2,000 to 2,993, the optimization program has greater incentive to allocate Soldiers to the E4 ranks.

Target Factors E3 and E4: The Target Factors Coefficients is designed to help separate the E3 and E4 ranks from the E5 and above ranks. Increasing the values of

Target Factors E3 and E4 from 0.10 and 0.10 to 0.16 and 0.72, respectfully, will make filling E3 and E4 ranks a higher priority in adjusting to the authorized targets. By the same token, reducing **Target Factors E9** from 1.00 to 0.72 will reduce the priority of filling the E9 ranks and allow more flexibility in the optimization to decrease the OSD in other areas of the program. It is possible that the increased reward given to **Promotion Factor E8** could be offsetting this reduction in another portion of the simulator and optimizer while still preserving the flexibility the reduction gives to **Target Factors E3 and E4**. Once again, more research could be devoted to this area of study.

SL1 Constraint: The Skill Level 1 constraint is used to balance the Skill Level 1 strength across grades E3 and E4. By lowering the coefficient value from 0.3 to 0.25 the ES program is adding more emphasis on the individual grades and not trying to combine the two.

BCT and OSUT Coefficients: The BCT and OSUT Coefficients are designed to generate a quadratic penalty for deviation from the ATRRS training accession program. By increasing the coefficient values from 31 and 33 to 44 and 41, respectfully, the penalty for failing to send Soldiers to training is increased and the ES program has more incentive to train Soldiers.

The changes to these eight coefficients will cause a reduction in the OSD by a significant amount. The common thread between these results is increased flexibility in the higher ranks and more focus in filling deviations in lower

ranks. The lower ranks have higher numbers of Soldiers and tend to carry much of the OSD value.

3. Exploratory Expansion of Results

The design of experiments for this thesis has all been directed towards the September 2009 data set, and this thesis has proven that by changing the coefficient values a lower OSD could have been achieved. Given this fact, the proposed changes to the coefficient values were sent to the Army G1, and they were asked to see if these values could be used on a different month’s data set. The Army G1 implemented these changes on the March 2010 data set and compared results to the different settings. The changes to the coefficients resulted in a reduction of the OSD from 3,761,887 to 3,060,009, which was an 18.7% drop in that month’s OSD level. This is an average drop of 8,355 mis-aligned Soldiers (equivalent to two combat brigades) a month for the seven year planning horizon. Although the coefficient changes have only been tested on two months worth of data (September 2009 and March 2010), in both cases there was a substantial drop in the deviation between authorizations and strength. Given that the model deviation resulting from the random numbers is small, these values are promising.

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V. CONCLUSIONS AND RECOMMENDATIONS

Conclusions to this thesis work and recommendations for future study are discussed in this chapter.

A. MANPOWER READINESS DISCUSSION

The work in this thesis was able to reduce the OSD from its current level by 14% for September 2009 and by 18% for March 2010 by changing a few of the objective function coefficients. By reducing the OSD, the on-hand quantity of Soldiers in the Army is more closely aligned with the authorizations and designated force-structure. This improved alignment increases the force manning by decreasing the overages and shortages the Army currently has within the force by the equivalent of two combat brigades.

The Army G1 now has different coefficient values they can use to potentially lower the OSD during future applications of the ES model. The full extent of the changes to the OSD based off the coefficient change will not be known until the output from the ES model is sent to the Analyst Projection Assistance System (APAS) in HRC. At APAS, they can look at the feasibility of implementation and an overall impact study can begin to calculate the full extent of what the changes mean in terms of resources, budget, and manning for the U.S. Army.

B. RECOMMENDATIONS FOR FUTURE STUDY

The coefficients obtained in this thesis were only applied to two months worth of data. Although in both cases, there was a significant drop in the OSD. Further

study is required to determine if the overall change is universal. Further research should be directed at looking at the first time this model was implemented with the original default values. Is it possible the coefficient values should have always been different from what the defaults are currently set to, or was there a major event such as force structure change or policy change that occurred and now change is required? Understanding those questions should lead to policy decisions on annual or periodical reviews of the model and additional experimentation to be conducted.

This thesis also looked at a subsection of the user inputs to the ES model. Further investigation on prioritizing the quantity of one MOS over another MOS, which is possible with the ES model, could be further examined. All MOSs in the Army are important, but there are some (Infantry, Military Police, etc.) that are more highly desirable than others. An analysis of the tradeoff between prioritizing one MOS over another could lead to new and insightful aspects to the ES model.

Another area of potential research is the identification of emerging trends. Can the ES model be used to identify emerging trends in data in a timely manner? If the ES model data is able to show trends in data before they are currently being detected, the Army G1 and HRC could be proactive in heading off potential problems. The ability to stop an area of concern before it expands to a major problem in the manpower arena can save the Army millions of dollars and improve force readiness. If you consider the cost of training and equipping a Soldier for a specialty that is

unknowingly going to be over strength in a year, and the cost of retraining that same Soldier once the realization is made the costs are extraordinary. In a major manpower program where the decisions made have lasting consequence, the ability to see trends and requirements early have great long term savings.

It should also be noted that this thesis had a very narrow focus on the values the 52 coefficients could take on during the course of experimentation. Future research in the area of acceptable inputs (minimum and maximum values) should be conducted. Finding the extreme values that can be used as inputs could give greater insight into the ES models behavior and lead to a more significant decrease in the OSD.

Another option for future research is in the model development. It is possible that the ES model has run its course and the G1 may need to begin looking at other ways of developing a seven year forecast. This could involve using a less complex model or replacing one or more components.

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APPENDIX. OBJECTIVE FUNTION COEFFICIENTS

Grade Coefficients	Min Range	Max Range	Default Value
Promotion Factors E3	-9999	9999	-120
Promotion Factors E4	-9999	9999	-4
Promotion Factors E5	-9999	9999	-4
Promotion Factors E6	-9999	9999	-4
Promotion Factors E7	-9999	9999	-4
Promotion Factors E8	-9999	9999	-4
Promotion Factors E9	-9999	9999	-4
Reclass Factors E3	0	9999	5000
Reclass Factors E4	0	9999	5000
Reclass Factors E5	0	9999	200
Reclass Factors E6	0	9999	200
Reclass Factors E7	0	9999	200
Reclass Factors E8	0	9999	200
Reclass Factors E9	0	9999	200
Strength Factors E3	-9999	9999	0
Strength Factors E4	-9999	9999	2000
Strength Factors E5	-9999	9999	3000
Strength Factors E6	-9999	9999	4000
Strength Factors E7	-9999	9999	5000
Strength Factors E8	-9999	9999	6000
Strength Factors E9	-9999	9999	7000
Target Factors E3	0.01	1	0.1
Target Factors E4	0.01	1	0.1
Target Factors E5	0.01	1	1
Target Factors E6	0.01	1	1
Target Factors E7	0.01	1	1
Target Factors E8	0.01	1	1
Target Factors E9	0.01	1	1

Non-Network Constraint Coefficients	Min Range	Max Range	Default Value
MOSS Shred Target	0	1	0.13
NCO Constraint	0	1	0
SL1 Constraint	0	1	0.3

Objective Function Arc Coefficients	Min Range	Max Range	Default Value
Conversion	-9999	0	-7500
MOS Deletion	-10	0	0
Demotions	-9999	0	-6000
LOSSES (ETS)	-9999	0	-9999
LOSSES (Other)	-9999	0	-9999
LOSSES (PML)	-9999	0	-50
LOSSES (Retirement)	-9999	0	-9999
LOSSES (Training)	-9999	0	-9999
Promotion (VBU)	-9999	0	-5000
Percent Bound on Pool Flows	0	100	100
Reclassification (Mandatory)	-9999	0	-9999
Reclassification (Reenlistee)	-9999	0	-9999
Reclassification (Voluntary)	0	9999	1
Same-Grade Reclassifications	0	9999	10
THS	-9999	0	-7100
BCT Training	0	9999	31
NPS Without Training	0	9999	3200
OSUT Training	0	9999	33
PS with Training	0	9999	34
PS Without Training	0	9999	3500
Training Deletions to Pools	0	9999	40

Table 10. Objective Function Coefficients with Minimum, Maximum, and Default Values

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LIST OF REFERENCES

Cashbaugh D., Hall A., Kwinn M., Sriver T., & Womer N. (2007). Chapter 13: Manpower and Personnel, Methods for Conducting Military Operational Analysis. *Military Operations Research Society*.

CPLEX users guide Web page. Retrieved May 14, 2010, from http://www.gams.com/dd/docs/solvers/cplex.pdf

Defense Manpower Data Center. Retrieved May 13, 2010, from http://siadapp.dmdc.osd.mil/personnel/MILITARY/ms0.pdf

Enlisted Jobs. Retrieved May 13, 2010 from http://usmilitary.about.com/od/enlistedjobs/tp/armyenlistedjobs.htm

G1 Mission Statement. Retrieved April 30, 2010 from http://www.armyG1.army.mil

Hall A. (2004). Validation of the Enlisted Grade Model Gradebreaks. *Winter Simulations Conference*, 921-925.

JMP®. Retrieved March 11, 2010 from http://www.jmp.com/support/downloads/documentation.shtml

Jones B., Johnson R.T, & Montgomery D.C. (2010). D-Optimal Latin Hypercube Design in review *Technometrics*.

Montgomery D.C. (2009). *Design and Analysis of Experiments 7th Edition*. New York: John Wiley & Sons.

Montgomery D.C., Peck E., & Vining G. (2006). *Introduction to Linear Regression Analysis*. New York: John Wiley & Sons.

Plackett R.L. & Burman J.P (1946). The Design of Optimum Multifactorial Experiments. *Biometrika* 33 (4), pp. 305-25, June 1946.

Title 10 United States Code. Retrieved May 12, 2010 from http://uscode.house.gov/download/title_10.shtml

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